College of Engineering, [1]Department of Computer Science and Engineering, [2]Department of Food, Agricultural and Biological Engineering

Image-Based Plant Leaf Disease Recognition with InceptionV3 Network

Zhengqi Dong[1], Dr. Darren Drewry[2]
{dong.760, drewry.19}@osu.edu

ABSTRACT

Background: Most traditional plant disease diagnosis strategies depend on human visual observation and inspection. However, this approach is time-consuming and requires significant human effort and expert knowledge. **Objective:** The recent advances in computer vision and deep learning provide a potential pathway to developing a plant disease diagnosis system that allows rapid detection of disease across large spatial areas with minimal human intervention. **Methods:** In this study, we developed a deep learning approach for plant leaf disease classification problems and conducted a range of experiments to quantify the performance of several state-of-the-art neural network architectures, including ResNet50, InceptionV3, and NASNet. All the experiments were trained on the PlantVillage dataset with 54305 images in total, spanning over 38 plant disease classes. We evaluated four different performance metrics to assess each architecture: accuracy, precision, recall, and area under the curve (AUC). **Results:** Our results showed that the InceptionV3 neural network architecture outperformed all other Convolutional Neural Network (CNN) architectures (ResNet50, NASNet-Large, NASNet-Mobile, MobileNet-v3-small, and MobileNet-v3-large) and produced a training accuracy of 94.14% and 97.94% over 6 epochs and 40 epochs of training, respectively. These results suggest that CNN architectures broadly, and the InceptionV3 model specifically, are capable of remote and automated plant disease detection. These results point to exciting future applications where lightweight smart phone applications or backend workstation developments can assist in plant leaf disease recognition problems, enhancing food production.

DATASET

- PlantVillage dataset published in 2015[1].
- Consists of over 54,305 images over 38 categories

Figure 1: 38 leaf image samples provided by PlantVillage dataset[2]

INTRODUCTION

Plant disease is a significant threat to food security, impacting both agricultural yield quantity and quality in an unpredictable way. The Food and Agriculture Organization estimates that diseases, insects, and weeds cause approximately 25% of global crop losses. In the United States, roughly $40 billion in crop yield losses are caused by plant diseases annually. In most developing countries, smallholder farmers play an essential role in global food production, but the traditional approaches in plant disease detection are expensive and time-consuming, which makes it impractical for smallholder farmers to adopt[4,5]. Therefore, an accurate and affordable plant disease diagnosis system is critical for identifying plant diseases at an early stage, allowing for mitigation efforts to control disease propagation. The recent improvement in deep learning algorithms, GPU performance, and the large scale of collected datasets provided a promising approach to achieve this goal cost effectively and efficiently.

Application Framework Design:

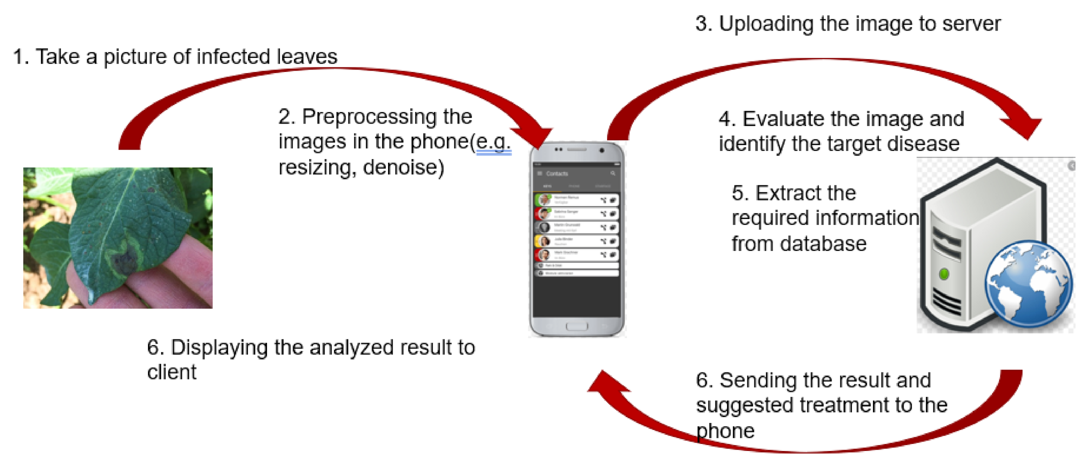

Figure 2: Proposed Application Framework for real-time plant disease detection[3].

Experimental Framework Design:

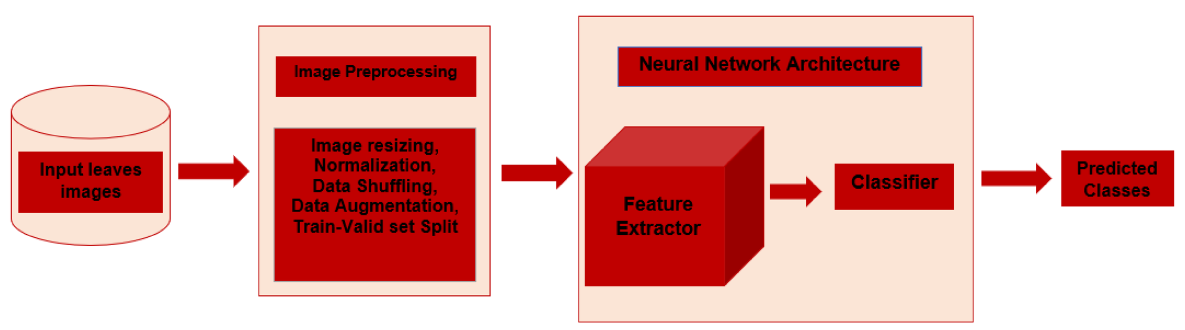

Figure 3: Pipeline of proposed deep learning training framework.

EVALUATION METRICS

- Precision:
  - $Precision = \frac{TP}{TP+FP} = \frac{TP}{Total\ positive\ result}$
- Recall
  - $Recall = \frac{TP}{TP+FN} = \frac{TP}{All\ result}$
- F1 Scores
  - $F1 = 2 * \frac{Precision * Recall}{Precision + Recall}$
- Accuracy
  - $Accuracy = \frac{\#\ of\ corrected\ prediction}{Total\ Samples}$
- Categorical Cross Entropy
  - $\text{Cross−Entropy(CE)} = -\sum_{i}^{C} \boldsymbol{y}_i log\left(f_i(\boldsymbol{x}_i; \boldsymbol{\theta})\right)$

RESULTS

Train-Validation Split Ratio Evaluation:

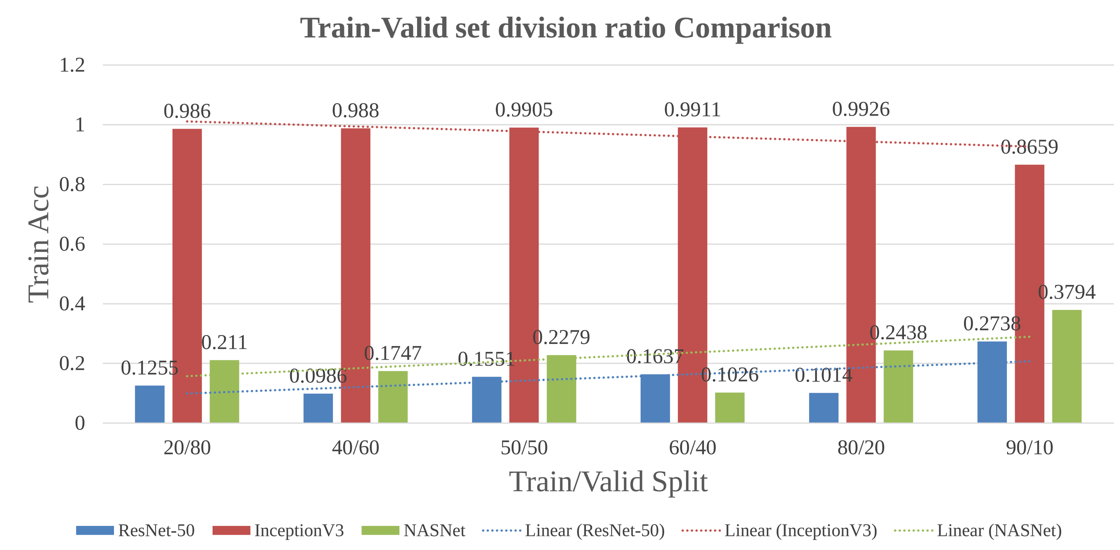

Figure 4: Evaluation of various train-validation split ratio on three different CNN models after 3 epochs of training.

Batch Size Evaluation:

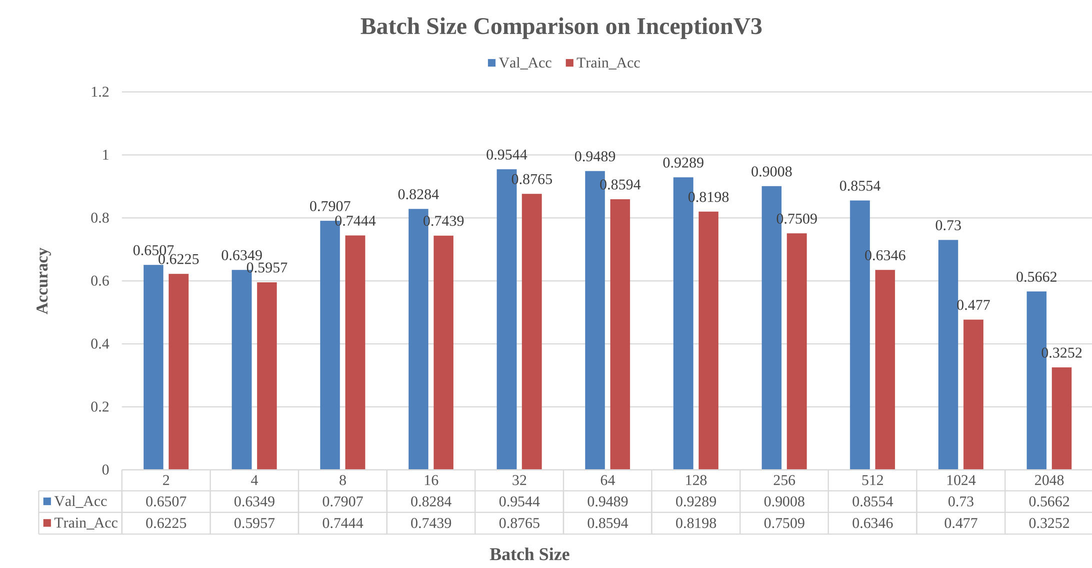

Figure 5: Evaluation of various batch size on InceptionV3 network after first epoch of training.

DNN Model Performance Evaluation:

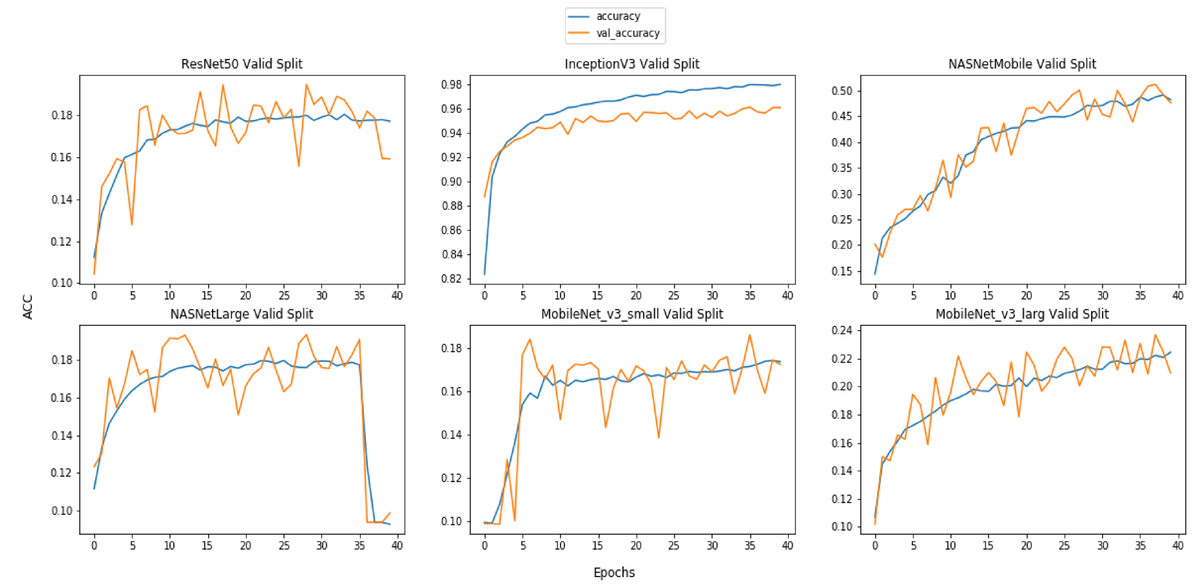

Figure 6: Training and validation accuracy evaluated on 6 different CNN models

DNN Model	Input size	Total Parameters	Trainable parameter	Throughput (s/epoch)	Train acc after 40 epochs(%)
ResNet-50	256x256x3	157,845,414	134,257,702	1099-1347	17.68
InceptionV3	256x256x3	97,340,230	75,537,446	1095-1374	97.94
NASNetMobille	256x256x3	73,515,706	69,245,990	1092-1270	48.27
NASNetLarge	256x256x3	349,197,944	264,281,126	1772-2135	9.27
MobileNet-v3-small	256x256x3	52,950,166	51,420,198	1894-3271	17.37
MobileNet-v3-large	256x256x3	88,152,486	83,926,054	2074-3196	22.45

Table 1: The pertinent configurations and performant results for 6 different CNN models.

CONCLUSIONS

- As the training ratio on the dataset increased, the training accuracy will increase. The best train-validation split ratio for our study is 80/20.
- As the batch size increased, the training accuracy for the model will increase. The best batch size for applying mini-batch gradient descent is 32 for our study.
- By comparing the performance of different size CNN models, no obvious linear correlation has found between the model complexity and their generalization ability.
- With the InceptionV3 neural network, the best performance we achieved after 40 epochs of training was 97.94% and 96.04% on the training and validation dataset, respectively, which outperformed other candidate models by a significant amount.
- Specifically, the InceptionV3 can achieve top-1 accuracy of 94.14% in training and 94.53% in validation over 2-hour of training and 97.94% in training and 96.04% in validation over 16-hours, respectively, on OSC Pitzer cluster with 48 cores of Dual NVIDIA Volta V100 GPUs, which suggests that the InceptionV3 model is suitable for both lightweight smart applications and backend workstation development within the context of plant leaf disease recognition.

REFERENCE

1. David P Hughes and Marcel Salathe. 2015. An open access repository of images on plant health to enable the development of mobile disease diagnostics. Arxiv (2015).
2. Sharada P. Mohanty, David P. Hughes, and Marcel Salathé. 2016. Using Deep Learning for Image-Based Plant Disease Detection. Front Plant Sci 7, (2016), 1419. DOI:https://doi.org/10.3389/fpls.2016.01419
3. Qian, Jianping, Xing, Bin, Wu, Xiaoming, Chen, Meixiang, & Wang, Yan'an. (2018). A smartphone-based apple yield estimation application using imaging features and the ANN method in mature period. Scientia Agricola, 75(4), 273-280. https://doi.org/10.1590/1678-992x-2016-0152
4. Federico Martinelli, Riccardo Scalenghe, Salvatore Davino, Stefano Panno, Giuseppe Scuderi, Paolo Ruisi, Paolo Villa, Daniela Stroppiana, Mirco Boschetti, Luiz R. Goulart, Cristina E. Davis, and Abhaya M. Dandekar. 2015. Advanced methods of plant disease detection. A review. Agron Sustain Dev 35, 1 (2015), 1–25. DOI:https://doi.org/10.1007/s13593-014-0246-1
5. WHO, IFAD, WFP, and UNICEF. 2020. The State of Food Security and Nutrition in the World 2020. FAO, IFAD, UNICEF, WFP and WHO. Retrieved from http://www.fao.org/documents/card/en/c/ca9692en

ACKNOWLEDGEMENTS

The author would like to thank Dr. Darren Drewry for the helpful advice and mentoring, which provides great support for the successful accomplishment of this project and thesis.